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THE ROLE OF SCENARIO UNCERTAINTY IN ESTIMATING THE BENEFITS OF CARBON MITIGATION*

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The benefits of carbon mitigation are subject to numerous sources of uncertainty and accounting for this uncertainty in policy analysis is crucial. One often overlooked source uncertainty are the forecasts of future baseline conditions (e.g., population, economic output, emissions) from which carbon mitigation benefits are assessed. Through, in some cases highly non-linear relationships, these baseline conditions determine the forecast level and rate of climate change, exposed populations, vulnerability, and way in which inter-temporal tradeoffs are valued. We study the impact of explicitly considering this uncertainty on a widely used metric to asses the benefits of carbon dioxide mitigation, the social cost of carbon (SCC). To explore this question, a detailed integrated assessment that couples economic and climate systems to assess the damages of climate change is driven by a library of consistent probabilistic socioeconomic-emission scenarios developed using a comprehensive global computable general equilibrium (CGE) model. We find that scenario uncertainty has a significant effect on estimates of the SCC and that excluding this source of uncertainty could lead to an underestimate of the mitigation benefits. A detailed decomposition finds that this effect is driven primarily through the role that uncertainty regarding future consumption per capita growth has on the value of inter-temporal tradeoffs through the consumption discount rate.

Keywords: Social cost of carbon; integrated assessment; scenario uncertainty.

Journal of Economic Literature Classification: Q51, Q54

1. Introduction

Climate change is one of the most important, but also vexing, problems of our time. Despite the complexity of the issue, inherent uncertainty, and considerable knowledge gaps policy makers are still left with the burden of having to make decisions as to the timing and magnitude of emission mitigation activities. To assist decision makers the research community has developed tools that seek to convey the current state of knowledge about potential welfare losses associated with greenhouse gas (GHG) emissions. These tools serve as only a single input into the process, but provide

*The views expressed in this paper are those of the author and do not necessarily represent those of the U.S. EPA. No Agency endorsement should be inferred.

valuable information about the quantifiable tradeoffs between policy alternatives. The social cost of carbon (SCC) is one of the most widely studied and used tools for this purpose. The SCC is a measure of society's willingness to pay to prevent the future damages that will arise from an incremental unit of carbon dioxide (CO_2) emissions (typically one metric ton) being emitted in a given year. As such, the SCC represents the initial Pigovian tax for negative externalities associated with carbon emissions. In principal, the SCC summarizes the impacts of CO_2 emissions on all relevant market and non-market sectors, including agriculture, energy production, water availability, human health, coastal communities, biodiversity, and so on. The SCC is of course limited by our knowledge of these complex systems, and is heavily influenced by the uncertainty surrounding the information we do have. An important role for policy analysts is to ensure that the central estimates and distributions of the SCC presented to policy makers correctly capture the known and quantifiable uncertainties associated with the problem.

Substantial effort has gone into understanding the role of uncertainty in the climate response to anthropogenic emissions (e.g., Newbold and Daigneault, 2009; Weitzman, 2009) and economics systems (e.g., Anthoff and Tol, 2013b) in determining the benefits of CO_2 mitigation as represented by the SCC. However, an often overlooked source of uncertainty are the economic, demographic, and emissions forecasts that define the baseline state of the world under which the impacts of climate change are being assessed. Through, in some cases highly non-linear relationships, these baseline conditions determine the forecast level and rate of climate change, exposed populations, vulnerability, and the way in which inter-temporal tradeoffs are valued. In many cases, estimates of the SCC are based on a single socioeconomic-emissions scenario, determined to be representative of the possible states of the world (e.g., Hope, 2013; Nordhaus, 2010). In other cases, sensitivity analysis has been performed and SCC estimates have been presented for multiple scenarios without a presumption of which might be more likely (e.g., Waldhoff *et al.*, 2011). In others cases, the SCC is estimated along multiple scenarios which are then, either explicitly or implicitly, given probabilities to generate an overall distribution (USG, 2010, 2013). What has not been studied in detail is the specific impact that uncertainty surrounding future socioeconomic and emissions forecasts has on the benefits of current carbon mitigation policies, as measured by the SCC. This paper provides initial insight into the way in which scenario uncertainty affects the SCC and the relative magnitude of that effect.

While a detailed analysis of the impact of scenario uncertainty on the benefits of carbon mitigation has not been previously conducted, there have been a few studies that incorporate a general representation of such uncertainty within a larger uncertainty analysis of the SCC. Newbold *et al.* (2013) and Anthoff and Tol (2013b) both include *ad hoc* representations of uncertainty around exogenous scenario forecasts though they take very different approaches. Newbold *et al.* (2013) specify probability distributions over the rate at which key socioeconomic variables, such as population and economic output per capita, will converge to deterministic long run values. Anthoff and Tol (2013b), on the other hand, allow the initial rate of growth in the state variables to be equal across potential scenarios and instead specify distributions for the long run differentiation in socioeconomic conditions. In both cases, the distributions that define uncertainty in future socioeconomic conditions are defined as independent for simplicity with the potential for internal inconsistencies arising in some simulations. Nordhaus (2011) offers slightly more consistency by defining distributions over key parameters (total factor productivity growth, population growth, carbon intensity of economic output) within a basic exogenous growth model to incorporate uncertainty about future socioeconomic conditions and CO_2 emissions into estimates of the SCC.

As noted by Newbold *et al.* (2013), a preferred approach would be to generate a set of probabilistic scenarios using a comprehensive computable general equilibrium (CGE) model that is capable of capturing key feedbacks and interdependencies across the sources of uncertainty. Assigning probabilities to a set of scenarios developed using a CGE model *ex post* will be, at least in part, an inherently arbitrary process. To define a defensible set of probabilities for scenarios one must account for the underlying uncertainty within the economic, social, and political systems in a systematic way and allow those assessments to determine the relative likelihood across a consistent set of forecasts. Recently Abt (2012) undertook such an exercise as a follow-up to the work of Webster *et al.* (2002). Using empirical assessments and expert elicitation to characterize key parametric and stochastic uncertainties associated with scenario development, they calibrated MIT's Emission Prediction and Policy Analysis (EPPA) global CGE model to develop sets of socioeconomic-emissions scenarios with explicit probabilities.

We adapt these libraries of scenarios for use with the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) integrated assessment model (IAM), which couples climate and economic systems to assess the monetized damages associated with anthropogenic GHG emissions. Using these libraries of probabilistic scenarios in conjunction with the FUND model, we assess the impact of uncertainty in socioeconomic-emissions forecasts on estimates of carbon mitigation benefits, as measured by the SCC. We find that incorporating uncertainty about future socioeconomic conditions significantly increases the expected benefits of carbon mitigation and that this effect is mainly through a desire for risk adverse agents to hedge against damages in cases of lower than expected per capita income growth. Specifically, we find a 10–35% ($3–$15) increase in the expected SCC estimates when socioeconomic uncertainty is considered and discounting is conducted in a manner that is theoretically consistent with the socioeconomic scenarios. Furthermore, we conduct a series of simulations, each of which considers different sources of uncertainty associated with climate damage assessment to disentangle the effect of different types of uncertainty on the SCC. We find that uncertainty surrounding baseline socioeconomic conditions may be more important for the SCC than uncertainty about the sensitivity of the climate to GHG emissions after which has often been noted as a key source of uncertainty.

Uncertainty in future GHG emissions is driven by uncertainty in both future socioeconomic conditions and potential climate polices. Therefore, it would be appropriate for a nation estimating the benefits of mitigation actions to consider a baseline in which there is uncertainty over future climate policies that are independent of the actions being analyzed. For example, when assessing the benefits of CO_2 mitigation, the U.S. government currently considers the possibility that in the baseline other nations/regions will adopt climate policies conditional on no further U.S. action beyond what is currently written into law. We specifically analyze the effect of such uncertainty on the SCC by further utilizing the work of Abt (2012) which used an expert elicitation to develop probability distributions over the effective carbon price in regions outside of the U.S. conditional on the assumption that the U.S. takes no further actions to significantly mitigate domestic emissions. We find that the low probability of meaningful action outside of the U.S. conditional on no further domestic action has a negligible effect on the SCC that should be used in U.S. benefit cost analysis.

We note that while this type of unidirectional soft-linkage between a CGE model and partial equilibrium IAM can provide valuable insight into the role of baseline scenario uncertainty on climate change mitigation benefits, there are limitations to the analysis. We have taken care to map key parameters (e.g., population, economic output, emissions) consistently across the models, however, there are other parameters and variables which may not be consistent across the models. For example, trends in energy efficiency technologies, preferences defining household energy demand, and the agricultural production functions. Part of this inconsistency is the result of using a unidirectional linkage such that the relative prices defining equilibrium in the CGE model represent a world without a changing climate. As noted by Carbone and Smith (2013), even outside of climate change, the general equilibrium effects of environmental changes may be non-trivial and the ideal would be to incorporate damages within a CGE model of behavior. However, in the case of climate change a bidirectional coupling of CGE and climate models is non-trivial and computationally burdensome in a deterministic setting. Adding uncertainty presents additional challenges. The main result of this paper, that uncertainty regarding future per capita income growth has a non-trivial impact on carbon mitigation benefits mainly through its effect on the certainty equivalent discount rate, is not negated by this caveat but future research incorporating climate damages into a CGE framework with uncertainty analysis may uncover additional effects of scenario uncertainty.

The remainder of the paper is structure as follows: Section 2 describes the set of probabilistic scenarios and the IAM used in our study. Section 3 presents the main results, and Sec. 4 provides concluding remarks.

2. Methods

In this section, we describe the methods and tools used to study the effects of scenario uncertainty on estimates of the SCC. We begin by presenting the suite of probabilistic socioeconomic-emissions scenarios used, followed by a brief description of the FUND IAM. The section concludes with a discussion of the techniques used to adjust the suite of probabilistic scenarios to be compatible with the FUND model.

2.1. *Probabilistic scenario libraries*

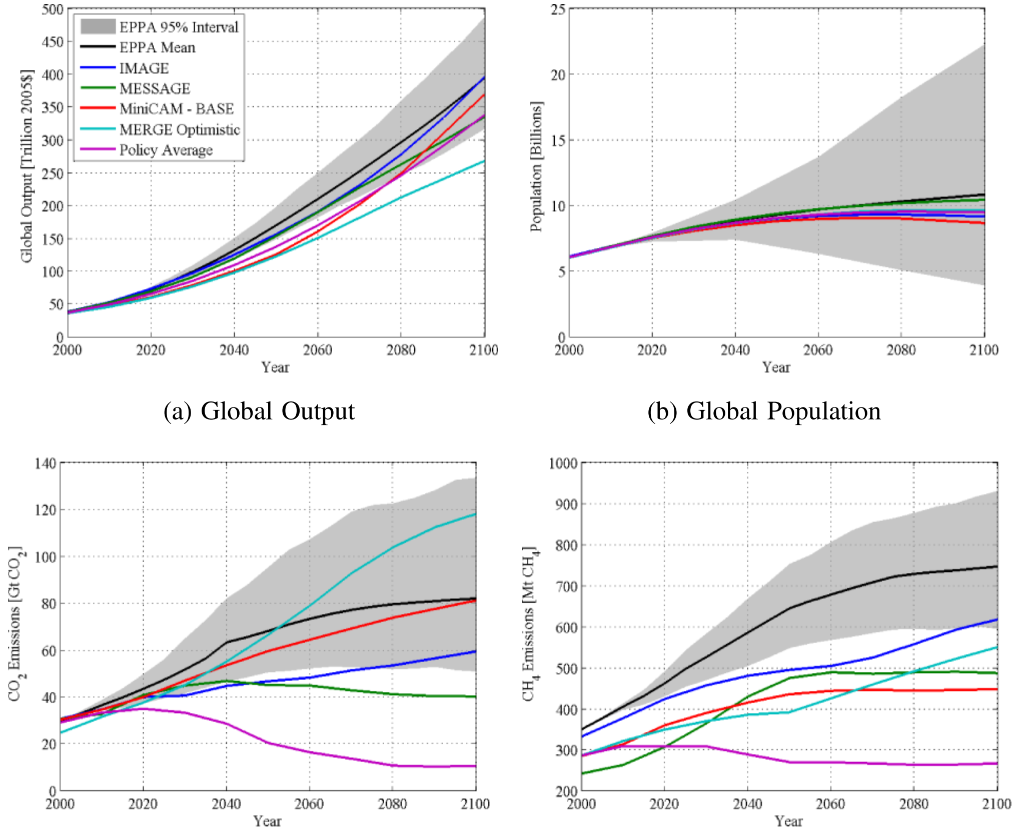
The foundation for the probabilistic socioeconomic-emissions scenarios are a set of libraries developed using MIT's EPPA model by Abt (2012) and available from the National Center for Environmental Economics at U.S. Environmental Protection Agency.[1] EPPA is a recursive dynamic global CGE model designed to generate projections of economic growth and anthropogenic emissions of greenhouse gases and aerosols (Paltsev *et al.*, 2005). The model includes 16 economic regions connected through international trade, and a relatively high resolution in the energy sector. To develop the libraries of probabilistic scenarios Abt (2012) defined probability distributions for key parameters of the model including: Elasticities of substitution, labor productivity growth, autonomous energy efficiency improvement, fossil fuel resource availability, population growth, urban pollutant trends, future energy technologies, non-CO_2 GHG trends, capital vintaging, and carbon prices outside of the U.S. The probability distributions were derived from a combination of empirical analysis and expert elicitation. To populate the scenario libraries the EPPA model was run 400 times using Latin-Hypercube sampling from the parameter distributions. Two separate libraries of potential baseline scenarios were developed: One with no additional climate policy in any region, and one with the possibility of non-U.S. climate action conditional on no new U.S. mitigation policies. Detailed information about the development of the probabilistic scenarios are available from Abt (2012).

Efforts to estimate the SCC have typically relied on deterministic socioeconomic-emissions scenarios, such as those from in the Special Report on Emissions Scenarios from the Intergovernmental Panel on Climate Change (Nakicenovic *et al.*, 2000) or those developed during exercises by the Stanford Energy Modeling Forum (EMF) (see Clarke *et al.* (2009) for a description of EMF-22). For example, both the 2010 and 2013 estimates of the SCC by the U.S. federal government were based on a set of five scenarios derived from the EMF-22 exercise (USG, 2010, 2013). These scenarios include four reference (business as usual) runs from the IMAGE, MESSAGE, MiniCAM — BASE, and MERGE Optimistic models.[2] The fifth scenario was an average of the 550 ppm CO_2−e stabilization without overshoot runs from the same set of four models. Each of the five scenarios was given equal weight (20% probability) in developing the final SCC estimates. Figure 1 provides a comparison between the library of probabilistic socioeconomic-emissions scenarios derived from the EPPA model and the five deterministic scenarios from the EMF 22 exercise used by the U.S. government.[3] We present this comparison to provide context for the uncertainty captured within the libraries of probabilistic scenarios.

[1] http://yosemite.epa.gov/ee/epa/eed.nsf/webpages/ClimateEconomics.html.

[2] The MiniCAM model is now known as GCAM but for consistency with the naming in the EMF 22 exercise and database, we use the MiniCAM notation in this paper.

[3] The library of EPPA scenarios presented in Fig. 1 is the one that includes the possibility of non-U.S. climate policies to provide a consistent comparison against the U.S. government's scenarios which also include such a possibility.



(a) Global Output

(b) Global Population

(c) Global CO_2 Emissions

(d) Global CH_4 Emissions

Figure 1. Comparison with the EMF 22 scenarios.

In general, the EPPA model is more optimistic about economic growth during the beginning to the middle of the century, though a number of the EMF 22 scenarios project higher economic growth during the later part of the century bringing levels in line by 2100. The five deterministic scenarios track the mean population projection in the EPPA library, but their range is very narrow relative to the 95% confidence interval contained within the probabilistic scenarios. The policy case used in the USG SCC estimates is substantially below even the lower end of the 95% confidence interval for the probabilistic scenarios suggesting the probabilistic scenarios place a far smaller probability on the possibility of substantial international climate action absent of further U.S. action.

For the probabilistic scenarios Abt (2012) determined the likelihood of non-U.S. climate policy through an expert elicitation from which regional and temporal conditional distributions for carbon prices outside of the U.S. were derived. The probability of significant mitigation policies being adopted outside of the U.S., under the condition of no further U.S. action, was deemed to be quite low by the expert panel and therefore

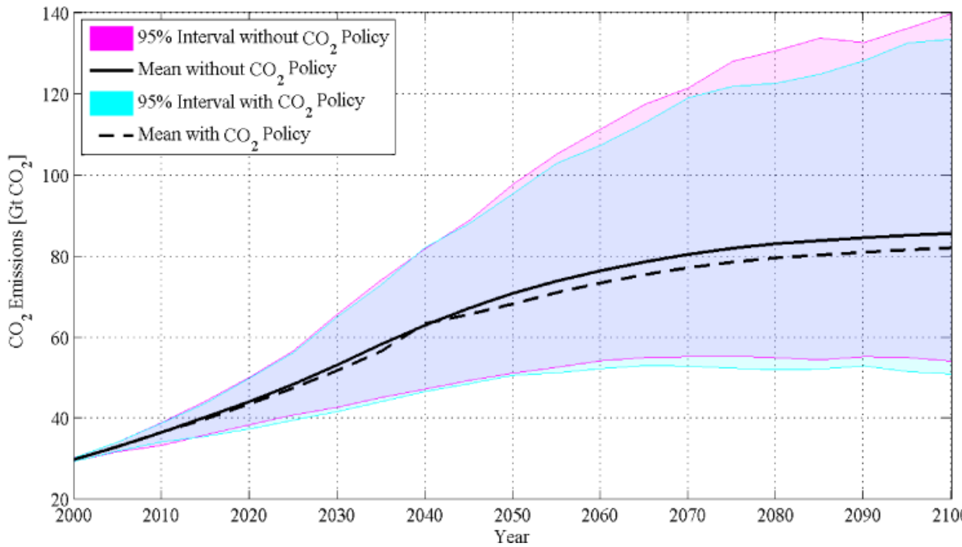


Figure 2. Effect of possible non-U.S. climate policy on global CO_2 emissions.

the two libraries of probabilistic scenarios are relatively similar. Figure 2 compares the projected global CO_2 emissions with and without the potential for non-U.S. carbon mitigation policies. The potential for such non-U.S. policy does not notably change the distribution of economic output forecasts and is assumed to have no effect on population. The inclusion of policy uncertainty has a small, but less than for CO_2, impact on global CH_4 emissions but the effect on other GHG emissions is negligible.

2.2. *FUND integrated assessment model*

The FUND IAM couples basic representations of atmospheric and climate systems with economic systems in order to estimate the monetized welfare impacts of climate change (Anthoff and Tol, 2013b). FUND has a spatial resolution of 16 national or multi-national regions and damage sectors spanning: Agriculture, forestry, sea level rise, cardiovascular and respiratory mortality and morbidity due to extreme temperatures, malaria, dengue fever, schistosomiasis, diarrhea, energy consumption for space heating and cooling, water resources, biodiversity loss, and tropical and extra-tropical storms. In this paper, we use version 3.8 of the model, for which the source code is available at http://www.fund-model.org along with more detailed technical information.

The model is run from 1950 onward to initialize the model in terms of both the climate and economic systems. For the economic systems this allows the model to resolve important lagged effects whereby the rate of climate change is important for understanding agents' ability to react. In the majority of cases the model's parameters are defined by probability distributions and therefore Monte Carlo simulations are used to estimate a sampling distribution of the net present value of climate change damages (the SCC). In this case, we use 10,000 simulations, which provide standard errors that are on the order of less than 2% of the mean SCC.

We maintain all of the default assumptions for the model's parameters except for the socioeconomic-emissions scenarios (including the starting regional population and economic growth), the endogeneity of emissions pathways, equilibrium climate sensitivity distribution, and the coastal protection algorithm. By default FUND is designed to estimate regional anthropogenic CO_2 emissions as proportional to economic output, where the proportion is based on the time period's energy and carbon intensity of production for the region. The growth rate of economic output, regional energy, and carbon intensity of production are specified exogenously, however, within the model the level economic output is adjusted based on the level of climate change induced damages in market sectors. This leads to realized emissions that are slightly different from the "no damage" emissions scenario that would be projected solely based on the exogenous inputs. This specification is potentially problematic as it does not take into account how climate change may alter the carbon intensity of production. For example, one of the most important damage categories within FUND is the increased demand for space cooling (Anthoff and Tol, 2013b). Since electricity generation is more carbon intensive per dollar of sales relative most household non-electricity consumption (Hassett *et al.*, 2009), it is likely that the CO_2 emissions associated with increased expenditures on electricity for space cooling due to climate change will be higher than the CO_2 emissions associated with the consumption that is displaced. However, the FUND model by default would assume that these changes lower emissions. Incorporating a more complete framework for endogenous emissions is beyond the scope of this paper, and therefore we chose to impose the emissions scenarios exogenously. We note that whether or not emissions are endogenized in the default manner used by FUND has a negligible effect on the mean SCC (significantly less than 1% in a default FUND run).

A key factor in determining the benefits of carbon mitigation is the response of the climate to GHG emissions. This characteristic of the climate is commonly represented through the equilibrium climate sensitivity which measures the increase in mean global and annual temperature in equilibrium from a sustained radiative forcing equivalent to a doubling of atmospheric carbon dioxide over pre-industrial levels. Measuring the aggregate strength of the numerous climate feedbacks is inherently uncertain and the distribution over potential values is often subject to a large variance and slowly diminishing upper tail (Roe and Baker, 2007). It has been shown that in some settings, even with only a small probability, the chance of a strong climate response to increasing atmospheric GHG concentrations has significant implications for the benefits of carbon pollution mitigation (Weitzman, 2009). To represent the equilibrium climate sensitivity we use a inverted truncated normal distribution as proposed by Roe and Baker (2007) based on the nature of the underlying uncertainty. The parameters of the distribution are calibrated based on the consensus statement by the Intergovernmental Panel on Climate Change in their Fifth Assessment Report (AR5) that the equilibrium climate sensitivity is "likely" between 1.5 C and 4.5 C (IPCC, 2007). Since the IPCC did not specify a central tendency in AR5, we refer to the analysis of the Coupled Model Intercomparison Project 5 by Forster *et al.* (2013) who found a mean equilibrium climate sensitivity of 3.22 C.[4]

The other modification we make to the FUND model is with respect to the algorithm used by the model to determine the behavior of regional decision makers in building coastal protections in response to expected sea level rise. By default FUND assumes decision makers that respond instantaneously to any annual change in the relevant state variables based on the assumption that these deviations from past trends will persist into perpetuity. This representation can lead to instability when considering scenario uncertainty that is, in part, determined by stochastic shocks.[5] Without modification some runs show regional decision makers moving from protecting a large proportion of their coast in one year, to stopping nearly all coastal protection programs in the next year, only to reverse that decision in the following year. We choose to avoid this instability by modeling regional decision makers as using a 20-year moving average of state variable trends when forecasting future conditions to determine coastal protection efforts. Appendix A has further details about adjustments made to the coastal protection algorithm and damages from sea level rise.

2.3. *Probabilistic scenario libraries for FUND*

The climate module within FUND requires specifications for global CO_2 emissions [Gt C], CH_4 emissions [Gt C], N_2O emissions [Mt N], SF_6 emissions [Mt SF_6], and SO_2 emissions [Mt S]. The economic module within FUND requires specifications for the regional population and gross domestic product (GDP) per capita growth rates. All specifications must cover the years 1950 onwards, in annual timesteps. The probabilistic scenario libraries described in Sec. 2.1 provide projections for all of these variables for the 16 EPPA regions between 1997 and 2100 in 5 year timesteps starting in 2000. To use the libraries of probabilistic scenarios with FUND, we need to map the projections from EPPA regions to FUND regions, construct pathways for the variables from 1950 to 2000, and extrapolate the scenario past 2100. We discuss each of these steps in turn.

2.3.1. *Mapping projections from EPPA to FUND regions*

The projections in the original library of scenarios described in Sec. 2.1 are available for the 16 regions modeled within EPPA. These regions are not the same as the 16 regions modeled within FUND. Table 1 lists the regions in each model. In some cases, EPPA

[4]Specifically the equilibrium climate sensitivity distribution is defined as $\lambda/(1-f)$, where $\lambda = 1.2$ C is the reference (grey-body) climate sensitivity and f is a normal random variable with mean 0.696 and standard deviation 0.389 truncated from above at 0.88. This provides a mean of 3.22 C and allows for approximately 66% of the mass to lie between 1.5 C and 4.5 C.

[5]The stochasticity is introduced in the development of the scenarios with EPPA and not within the FUND model itself.

Table 1. Regions in the FUND and EPPA models.

FUND Regions		EPPA Regions	
Region	Abbreviation	Region	Abbreviation
United States	USA	United States	USA
Canada	CAN	Canada	CAN
Western Europe	WEU	European Union	EUR
Former Soviet Union	FSU	Former Soviet Union	FSU
Australia and New Zealand	ANZ	Australia and New Zealand	ANZ
China Plus	CHI	China	CHN
Japan and South Korea	JPK	Japan	JPN
Central and Eastern Europe	EEU	Eastern Europe	EET
Middle East	MDE	Middle East	MES
Central America	CAM	Mexico	MEX
South America	LAM	Central and South America	LAM
South Asia	SAS	India	IND
Southeast Asia	SEA	Indonesia	IDZ
North Africa	MAF	Higher Income East Asia	ASI
Sub-Saharan Africa	SSA	Africa	AFR
Small Island Nations	SIS	Rest of World	ROW

regions are a direct, or fairly comparable, match to a region in FUND. These include the United States, Canada, Western Europe, the Former Soviet Union, China Plus, and Australia and New Zealand. In the case of Western Europe there are some small discrepancies, such as whether the Channel Islands are included, but these differences are negligible relative to the region. In the case of China Plus, FUND includes Macao, Mongolia, and North Korea whereas those are listed in the "Rest of World" region in EPPA. Since these countries represent a negligible percentage of the region's level in any of the scenario variables, we consider them sufficient to be considered a direct mapping. For the remainder of the FUND regions, we adopt the mapping in the last column of Table 2. This represents the most parsimonious mapping possible.

In order to calibrate the mapping parameters we use country level projections for the scenario variables (population and GDP per capita growth). This data is aggregated up to the regional scale for both the FUND and EPPA regions and used to directly solve for a set of mapping parameters. To calibrate the population and GDP per capita mapping parameters we use the CEPII database reflecting country level projections out to 2050 (Foure *et al.*, 2012). The parameters we use in our regional mapping are defined as the average projected in the CEPII database between the years 2000 and 2050. This approach implicitly assumes that shifts in the regional variables will be spread evenly across the countries within the EPPA regions.[6] The specific estimates for

[6]We considered alternative specifications that allow for the mapping parameters to shift with the level of regional variables but found such definitions to be unstable for the tails of the EPPA scenario distribution.

Table 2. Regional mapping from EPPA to FUND.

FUND Region	EPPA Mapping
USA	USA
CAN	CAN
WEU	EUR
FSU	FSU
ANZ	ANZ
CHI	CHN
JPK	JPN + α_1ASI
EEU	EET + α_2ROW
MDE	MES + α_3ROW
CAM	α_4(MEX + LAM)
LAM	$(1 - \alpha_4)$(MEX + LAM)
SAS	IND + α_5ROW
SEA	IDZ + $(1 - \alpha_1)$ASI + α_6ROW
MAF	α_7AFR
SSA	$(1 - \alpha_7)$AFR
SIS	$(1 - \alpha_2 - \alpha_3 - \alpha_5 - \alpha_6)$ROW

Table 3. EPPA to FUND mapping parameters.

Parameter	Population	GDP
α_1	0.178	0.579
α_2	0.005	0.011
α_3	0.118	0.559
α_4	0.281	0.340
α_5	0.643	0.290
α_6	0.188	0.115
α_7	0.154	0.291

the mapping parameters are presented in Table 3. Since the climate model in FUND is resolved based on global emissions we do not specify mapping parameters for emissions data.

2.3.2. *Historic scenario*

In order to calibrate the historic (1950–1997) population, we use the United Nations Population Division database (UN, 2013) to derive estimates of the population growth rate for the FUND regions. These growth rates are used to define the historic population scenario based on the regional populations in 1997 as derived in Sec. 2.3.1. To calibrate historic GDP, we use the timeseries of GDP and population estimates from Maddison (2003) to derive GDP per capita growth rates for the FUND regions. These growth rates are then applied to the 1997 levels of population and GDP derived in Sec. 2.3.1 to produce a historical GDP scenario. For consistency, we use the historical emissions data from Asadoorian *et al.* (2006) which was designed to match up with emissions forecasts from the EPPA model. Since the FUND climate model is resolved from global emissions no further assumptions about regional mappings are required.

2.3.3. *Extrapolation past 2100*

The EPPA scenario libraries are only computed out to the year 2100 but given the long-term nature of the climate change problem, we run the FUND model out to 2400 to capture the long-term impacts of carbon emissions. This process requires extrapolating the scenarios past 2100. We adopt reasonable central assumptions that have been used elsewhere in the climate economics literature, but note that clearly any forecast out this far in time will be fraught with uncertainty. Therefore, we examine the sensitivity of our results to these assumptions by considering uncertainty over these extrapolations as represented by wide uninformed priors.

It has often been noted that in the long-term there are reasons to expect a decline in the global GDP per capita growth rate relative to current conditions. Some have argued this on the basis that current rapid growth in (some) developing nations, in part fueled by knowledge and technology transfers, will converge to that of developed nations (Lucas, 2000; Helpman, 2009). Others have suggested that finite supplies of natural resources will ultimately place constraints on perpetual economic growth (Meadows *et al.*, 2004). Following Newbold *et al.* (2013), we assume a long run GDP per capita growth rate of 1%, which we implement through a linear decline from 2100 to 2300. When considering uncertainty over the long-term GDP per capita growth rate, we use a uniform distribution ranging from 0% to 2% with the lower bound being consistent with the assumptions of USG (2010) and an upper bound representative of the average global growth rate over the past six decades (Maddison, 2003). This range is also inclusive of the assumptions made in other climate economics studies (e.g., Nordhaus, 2010; Anthoff and Tol, 2013b).

Long-term exogenous population projections used in climate economics and elsewhere, tend to be based on reaching a replacement fertility rate where the population growth rate ultimately becomes zero. While there seems to be some comfort with this general assumption, with Cohen (1995) going so far as to suggest that it is “the one irrefutable proposition of demographic theory,” the point in time at which the replacement rate is reached can vary widely between projections. For our central tendency, we follow USG (2010) in assuming the population growth rate will reach zero in 2200, an assumption similar to the projection of Nordhaus (2010). For simplicity, we implement this assumption as a linear decline from the 2100 growth rate. When considering uncertainty over this assumption we use a uniform distribution ranging from 2150 to 2250. The lower end of this range is similar to assumptions by Anthoff and Tol (2013b) and the upper end is consistent with an extrapolation of an exponential decline in the population growth rate based on projections by the The World Bank (2013).

Changes in the CO_2 emissions intensity (CO_2 per unit of economic output) are the result of numerous factors including relative energy trends, technological change, and governmental policies. As noted by Nordhaus and Boyer (2000), in the long run baseline CO_2 emissions intensity will be driven by the escalating price of carbon based fuels due increasing scarcity and extraction costs and the declining price of non-emitting energy sources due to technological advancements. Following Nordhaus (2010), we assume that CO_2 emissions intensity reaches zero in 2250 as non-emitting technologies become cheaper than the remaining fossil fuel resources. For simplicity, we implement this transition from the 2100 CO_2 emissions intensity linearly. When considering uncertainty over this assumption, we use a uniform distribution over the year in which the economy reaches decarbonization in the baseline with a range of 2150 to 2350. For non-CO_2 emissions, we assume that they remain constant at their 2100 levels as this assumption has little effect on the mean social cost estimates compared to alternative assumptions.

We recognize that there is the potential for correlations between these distributions and the potential for further study to provide improved assessments of the underlying distributions of these extrapolation assumptions. We do not present these assumptions as a state-of-the-art assessment or the most defensible approach to extrapolate socio-economic and emissions projections far out into the future. Instead we suggest that these assumptions are a reasonable approach to scope out the impact of such uncertainty where the results may be used to inform the value of future efforts to study alternative approaches and calibrations.

3. Results

Uncertainty surrounding the benefits of mitigating CO_2 emissions arises from a number of sources in addition to the forecasts of future socioeconomic and emission trajectories. Two of the most notable sources are the strength of the climate response to GHG emissions and the mapping of climate change to human well being. As discussed previously, the FUND model incorporates uncertainty over the strength of the climate response through the equilibrium climate sensitivity distribution and uncertainty over the welfare impacts of climate change by defining probability distributions for most of the parameters in the model's damage functions. We denote this case with uncertainty only over the equilibrium climate sensitivity and damage parameters as the default case as this is the standard for most probabilistic analyses of the SCC. We begin by incorporating additional uncertainty regarding socioeconomic scenarios, post-2100 extrapolation uncertainty, and non-U.S. climate policy conditional on no further U.S. action to the default case to understand their impact.[7] To place the effect of socio-economic, extrapolation, and non-U.S. policy uncertainty in context we then consider a

[7]We note that uncertainty in socioeconomic conditions will also lead to uncertainty in emissions but refer to this source as socioeconomic uncertainty to denote the difference from policy uncertainty.

breakdown of the effect of uncertainty over climate sensitivity and the damage parameters on the SCC.

Given the important role of discounting in the estimation of the SCC, we consider a series of five specifications to understand important interactions between the underlying assumptions of social preferences and the sources of uncertainty. The per period consumption rate of discount, r_t, used in estimating the SCC is defined based on the Ramsey formula

$$r_t = \rho + \eta g_t, \tag{1}$$

where ρ is the pure rate of time preference, η is the elasticity of marginal utility of consumption, and g_t is the growth rate of per capita consumption in period t. We consider four variable discount rates based on commonly applied values for ρ (1% and 0.1%) and η (1.0 and 1.5). We also consider a constant discount rate of 3% (mathematically represented as $\rho = 0.03$ and $\eta = 0$) to understand how the correlation between the consumption rate of discount and socioeconomic conditions influences the impact of scenario uncertainty on the SCC.

The main results of this paper are presented in Table 4, which lists the mean (and standard errors) for the SCC estimates in 2015 for the default case considering uncertainty only over climate sensitivity and the damage parameters and the cases where additional sources of uncertainty are included.[8] The results for the default case are comparable to the most recent published estimates based on the FUND model (Anthoff and Tol, 2013a). The impact of incorporating socioeconomic uncertainty may be seen

Table 4. Mean SCC in 2015 with standard error [2007\$ per ton CO_2].

ρ	η	Default	Added uncertainty		
			Socioeconomic	Socioeconomic and extrapolation	Socioeconomic and policy
0.010	1.5	14 (0.2)	18 (0.4)	18 (0.4)	17 (0.3)
0.001	1.5	45 (0.8)	60 (1.5)	61 (1.7)	58 (1.3)
0.010	1.0	34 (0.4)	37 (0.6)	37 (0.6)	36 (0.5)
0.001	1.0	127 (1.7)	140 (2.5)	141 (2.9)	136 (2.3)
0.030	0.0	20 (0.2)	20 (0.2)	21 (0.2)	20 (0.2)

[8]In this paper, we present results for the expected SCC, which for a given social welfare function W, path of emissions x, and path of per capita consumption, c, is defined as $\overline{\mathrm{SCC}}_t = E[\partial W/\partial x_t / \partial W/\partial c_t]$ for a perturbation in year t. To date, the expected SCC has been the primary metric used in analysis to support and inform policy decisions. However, common in the literature are results for the certainty equivalent SCC, defined as $\mathrm{SCC}_t = \partial E[W]/\partial x_t / \partial E[W]/\partial c_t$, which is more theoretically consistent with goal of maximizing expected welfare under uncertainty. Conditional on a specific set of preferences the two metrics are related, such that $\mathrm{SCC}_t = \overline{\mathrm{SCC}}_t + \mathrm{Cov}(u_t', \hat{\mathrm{SCC}}_t)/E[u_t']$, where u_t' is the marginal utility of consumption at the time of the perturbation and $\hat{\mathrm{SCC}}_t$ is the SCC for a specific realization of the world. For contemporary values of t, such as those studied in this paper, there is little uncertainty about u_t' in the modeling and therefore the expected SCC and certainty equivalent SCC are not notably different. As such, the conclusions of this paper are not influenced by the choice of metric.

by comparing the results in the fourth column to those of the default case. To understand the role of socioeconomic uncertainty on the SCC estimates consider that the relative effect is strongly driven by the value of η, such that for the constant discount rate introducing socioeconomic uncertainty has no effect, around a 10% effect for a value of $\eta = 1.0$, and an effect of around 30–35% in the case of $\eta = 1.5$. These results suggest that the primary effect of considering uncertainty in forecasts of baseline conditions occurs through its role in determining the effective consumption discount rate. Uncertainty over future income growth leads to an increases in the willingness to sacrifice in the current period to hedge against the potential that additional damages (in this case from climate change) will be born in future periods with lower than expected per capita consumption growth (Gollier, 2008). This leads to an increase in the estimate of the mean SCC. Because the parameter η defines the concavity of the utility function in this setting, it also defines the representative agent's level of risk aversion. Therefore, the relative effect of socioeconomic uncertainty increase with η as suggested by the theoretical work of Gollier (2007).

To further examine this effect of socioeconomic uncertainty we follow Weitzman (1998) and consider the certainty-equivalent forward rate for discounting between adjacent periods

$$\tilde{r}_t = -\frac{dE[P_t]/dt}{E[P_t]}, \tag{2}$$

where $E[P_t]$ is the expected discount factor

$$E[P_t] = E\left[\exp\left(-\sum_{s=1}^{t} r_s\right)\right], \tag{3}$$

and r_s is the consumption discount rate as defined in (1). We then define the certainty equivalent consumption discount rate for discounting period t back to the present as

$$\hat{r}_t = \frac{1}{t}\ln\left(\prod_{s=0}^{t}\exp(\tilde{r}_s)\right).$$

Figure 3 presents the certainty equivalent consumption discount rate under the $\rho = 0.001$ and $\eta = 1.5$ specification for the deterministic (all parameters at their mean), the default case with uncertainty over climate sensitivity and the damage parameters, and the case where socioeconomic uncertainty is added to the default case.[9] Even for completely deterministic setting the consumption discount rate still declines over time due to a population growth rate that is higher than the economic growth rate, leading to declining consumption per capita growth over the time horizon. When uncertainty over

[9]The initial drop in the certainty equivalent consumption discount rate from approximately 3.7% in 2015 to 3.5% in 2020 is a byproduct of the 5 year timestep within the EPPA model used to develop the scenarios. Future effects of the 5 year timestep are smoothed out as a result of the certainty equivalent consumption discount rate definition.

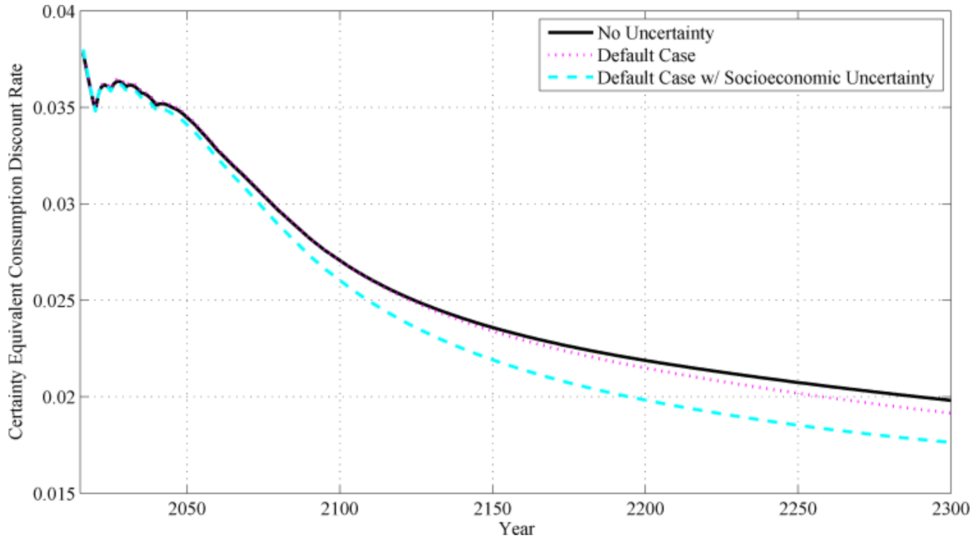


Figure 3. Certainty equivalent consumption discount rate ($\rho = 0.001$, $\eta = 1.5$).

climate sensitivity and the damage parameters are considered the certainty equivalent discount rate falls slightly in the long-term as uncertainty over climate damages leads to some uncertainty over economic growth due to their feedback effect. However, with the inclusion of uncertainty over socioeconomic forecasts the certainty equivalent discount rate is significantly lower. By 2200, the certainty equivalent discount rate is around 10% lower when socioeconomic uncertainty is considered compared to the default case. This decrease in the effective discount rate results in the main source of the increase in the estimates of the mean SCC seen in Table 4.

Our core finding, that uncertainty over the forecast of the socioeconomic scenarios affects the SCC primarily through the consumption discount rate, can be further illustrated by considering the simulated SCC distributions. We compare the typical default case studied with uncertainty over equilibrium climate sensitivity and damages function parameters to the addition of socioeconomic uncertainty. Figure 4 presents the simulated 2015 SCC distributions for both the case of a variable discount rate (Fig. 4(a)) and a constant discount rate (Fig. 4(b)). As may be seen, in the case of the constant discount rate there is no significant change in the shape of the distribution and in turn the mean SCC. However, in the case of the variable discount rate there is a significant increase in the variance of the SCC estimates. This is evident by the increase in the mass at both the upper and lower tails of the distribution. In terms of the effect on the mean SCC, the increase in the upper end of the tail dominates.

In column five of Table 4 uncertainty over the post-2100 extrapolation assumptions is introduced to the default case with socioeconomic uncertainty. This additional uncertainty increases the expected SCC estimates by less than 2% despite the wide range of scenario uncertainty introduced. Furthermore, in all discounting specifications the increase in the mean SCC is within the standard error of the estimates. This result

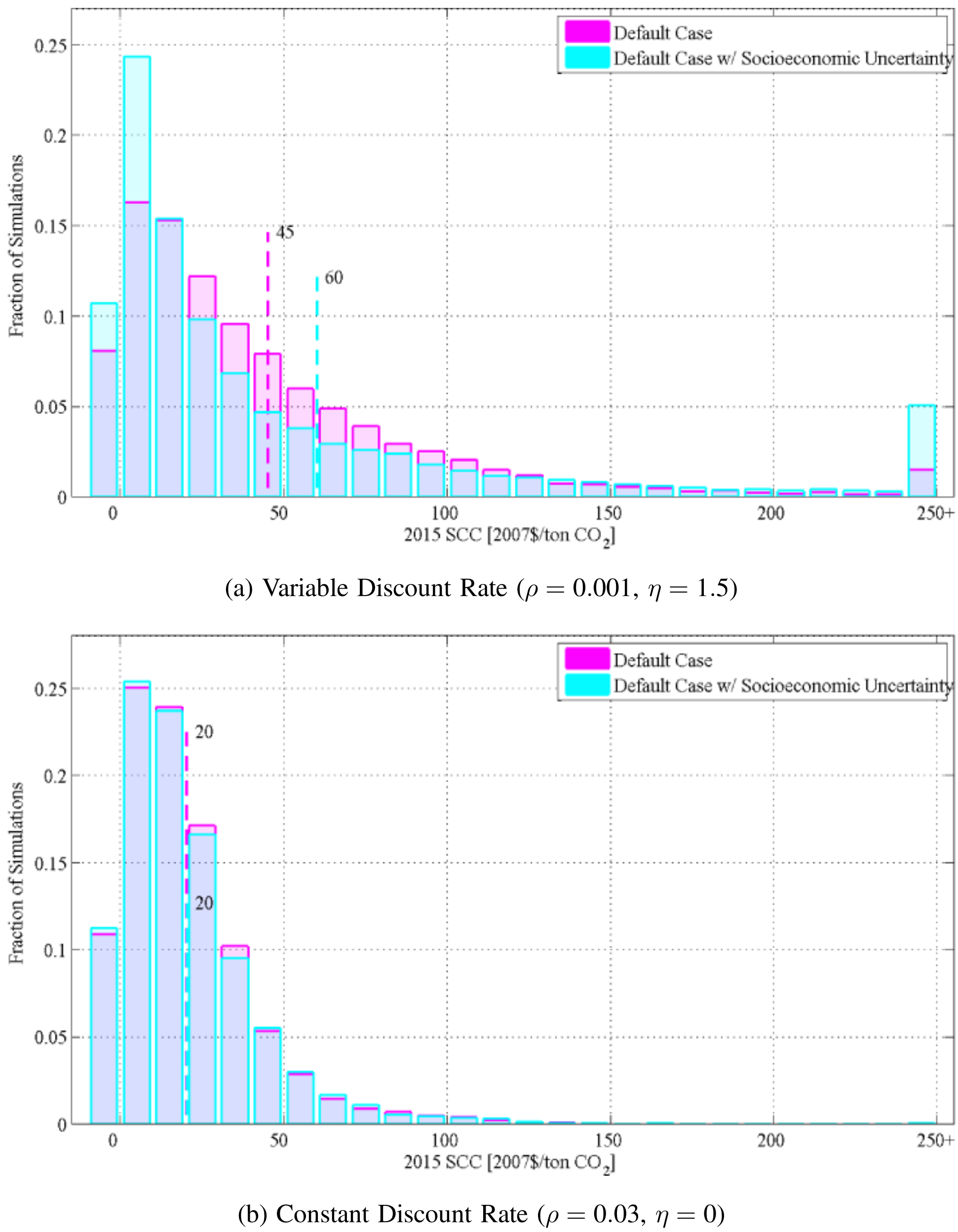


Figure 4. Effect of scenario uncertainty on the 2015 SCC distribution.

suggests that for the purpose of estimating the benefits of near term CO_2 mitigation on the margin, uncertainty over the baseline socioeconomic and emissions conditions past 2100 may not have a significant role in determining the mean SCC estimates. It is important to note that this result does not suggest that the events past 2100 are irrelevant for estimating the SCC. For the central cases of this paper, 50–85% of the mean SCC estimates are due to the perturbation's incremental damages past 2100,

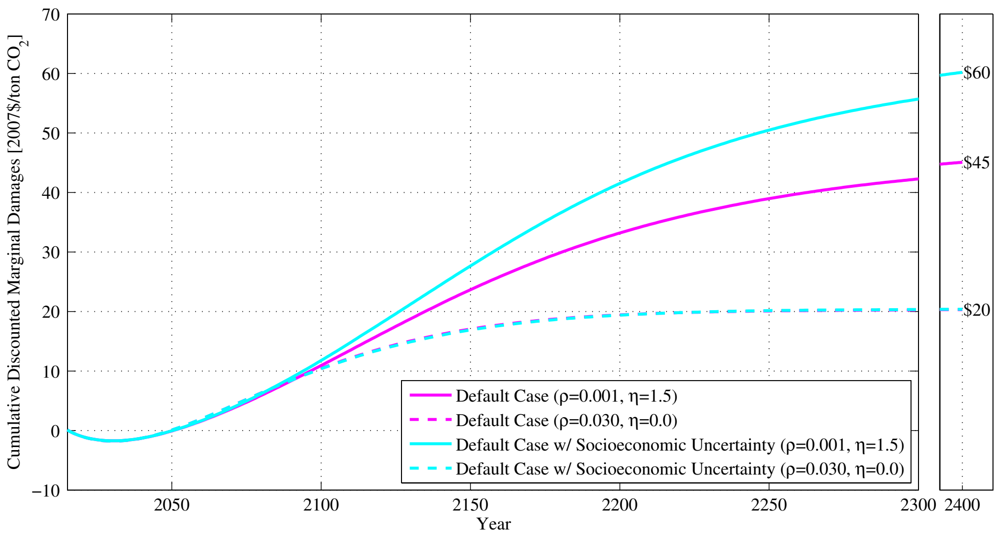


Figure 5. Cumulative discounted mean damages over time for a perturbation in 2015.

depending on the discounting specification. Figure 5 presents the cumulative discounted marginal damages associated with a perturbation in 2015.

In column six of Table 4, we add in the probability of climate policy outside of the U.S. conditional on no additional GHG mitigation policies within the U.S. as described in Sec. 2.1. Given the very low probability assigned by the expert panel to the possibility of significant mitigation action outside the U.S., the results in Table 4 are as expected with the additional non-U.S. climate policy uncertainty having only a small effect on the mean SCC. This result is relatively constant across the entire SCC distribution as is shown in Fig. 6. In most cases there is a slight decrease in the mean SCC when the non-U.S. climate policy uncertainty is included, but this difference is close to the standard error in magnitude except for the case with a relatively low effective discount rate.

3.1. *Comparison to other sources of uncertainty*

To put the effect of socioeconomic uncertainty in context, we consider a decomposition of the SCC estimates in the default case based on the two major sources of uncertainty traditionally considered: equilibrium climate sensitivity and the damage function parameters. Table 5 lists the mean (and standard errors) for the 2015 SCC estimates under three additional specifications in addition to the default case. The third column considers the deterministic case where all parameters are set at their mean values. By comparing these deterministic estimates with the default cases in the last column it may be seen that including uncertainty over damage parameters and the equilibrium climate sensitivity increases the expected value of the SCC by around 80–105%.

The other two cases presented in Table 5 consider including only a single source of uncertainty to provide insight into the relative effect of the two sources included in the

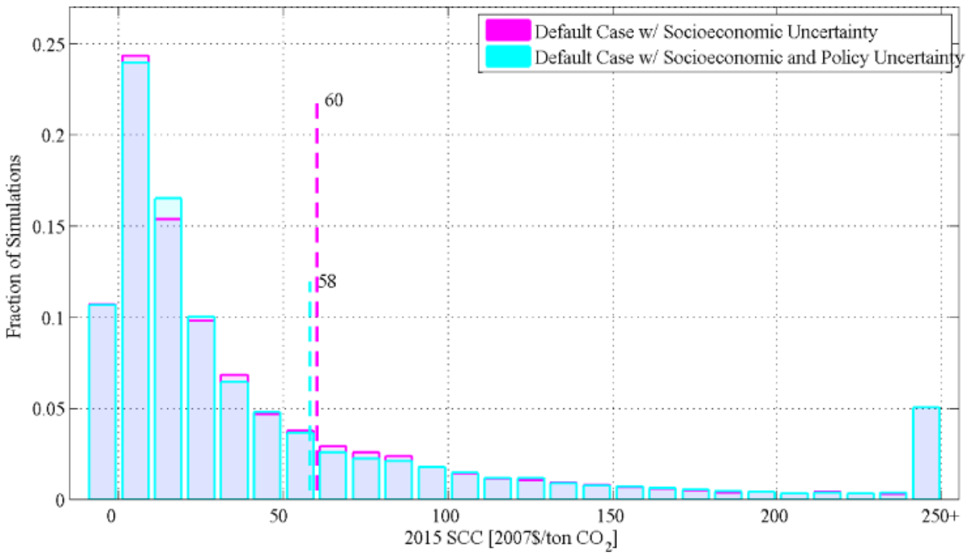


Figure 6. Effect of non-U.S. policy uncertainty on the 2015 SCC distribution ($\rho = 0.001$, $\eta = 1.5$).

Table 5. Mean SCC in 2015 with standard error [2007$ per ton CO_2].

ρ	η	Uncertainty included			
		None	Damage parameters	Climate sensitivity	Damage parameters and climate sensitivity (Default)
0.010	1.5	7	17 (0.2)	6 (0.0)	14 (0.2)
0.001	1.5	22	50 (0.5)	20 (0.2)	45 (0.8)
0.010	1.0	18	40 (0.4)	15 (0.1)	34 (0.4)
0.001	1.0	65	137 (1.2)	63 (0.6)	127 (1.7)
0.030	0.0	11	25 (0.2)	11 (0.0)	20 (0.2)

default case. The inclusion of uncertainty over the equilibrium climate sensitivity, in the fifth column, places a small amount of downward pressure (5–15%) on the mean SCC. This stems, in part, from the fact that FUND forecasts some benefits at low levels of warming due to increased productivity in the agricultural and forestry sectors and reduced demand for space heating. As a result, the annual damages in FUND are decreasing with respect to the equilibrium climate sensitivity parameter in the near term, an effect which helps net out future increases in damages from higher levels of warming due to discounting.[10] It is the incorporation of uncertainty over the

[10]We note that this result may be, in part, driven by a temperature response function within the FUND model that has been shown to be less responsive to uncertainty over the equilibrium climate sensitivity than would be expected, particularly for high values (Marten, 2011).

parameters of the damage functions that has the greatest impact on the mean SCC estimates. Moving from the deterministic case to one in which only damage function uncertainty is considered, in the fourth column, increases the mean SCC estimate by 110–140%.

4. Concluding Remarks

The benefits of carbon mitigation are subject to numerous sources of uncertainty, and accounting for this uncertainty in policy analysis is crucial. One often overlooked source uncertainty is the forecast of future baseline conditions from which carbon mitigation benefits are assessed. Baseline characteristics of concern include regional assessments of economic activity, population growth, and emissions of GHGs and tropospheric aerosols. Through, in some cases highly non-linear relationships, these baseline conditions determine the forecast level and rate of climate change, exposed populations, vulnerability, and way in which inter-temporal tradeoffs are valued. We study the impact of explicitly considering this uncertainty on a widely used measure for the benefits of CO_2 mitigation, the SCC. We use a detailed IAM that couples economic and climate systems to assess the damages of climate change in conjunction with a library of consistent probabilistic socioeconomic-emission scenarios to explore this question.

Our results show that assuming a deterministic central estimate for the future socioeconomic state of the world may lead to a significant underestimate of the expected benefits of carbon mitigation. Specifically, we find a 10–35% ($3–$15) increase in the expected SCC estimates when socioeconomic uncertainty is considered and discounting is conducted in a manner that is theoretically consistent with the socioeconomic scenarios. We find that the impact of excluding uncertainty about future socioeconomic conditions could be larger than the impact associated with excluding uncertainty about the sensitivity of the climatic response to GHG emissions. Furthermore, we find that the uncertainty about future socioeconomic conditions may be substantially more important for assessing intertemporal tradeoffs, as defined by the effective consumption discount rate, than for assessing the vulnerability of regions and sectors to forecast climate changes. The relative impact of this effect is higher in cases with a higher rate of relative risk aversion, as there is a greater desire to hedge against the possibility of experiencing climate damages in cases of lower than expected income per capita growth.

We also consider the impact of allowing for the possibility of additional regional or international carbon policy conditional on the assumption that the U.S. takes no further action to significantly reduce GHG emissions. Allowing for this additional policy uncertainty has little to no effect on the distributions of economic activity and population, and only a minimal change in global CO_2 emissions. Our results suggest that the expected SCC estimates are not affected by the inclusion, or conversely the exclusion, of such uncertainty. The small size of the effect is primarily driven by the low conditional probability placed on significant international action absent U.S. involvement by the expert panel that was convened by Abt (2012) to develop the set of probabilistic scenarios. Given the negligible quantitative effect of such uncertainty, the inherent issues associated with assessing the conditional regional carbon price distributions, and the resulting nation specific SCC estimates it may be preferable to exclude such policy uncertainty in estimates of the SCC.

The FUND model used in this paper represents a detailed accounting of what we currently know and can reasonably quantify about the potential damages associated with future climatic changes. For this reason, it has been widely used throughout the academic community (Tol, 2008) and by governments (USG, 2013). However, it is only one of a handful of models that have been proposed to estimate the SCC. A main difference between models is that FUND is based on a detailed sectoral accounting of damages whereas other models, such as those by Nordhaus (2010) and Hope (2013), estimate damages as a proportion of regional GDP. While this difference in model structure will not affect the impact socioeconomic uncertainty has on the effective discount rate, it could lead to additional effects on the SCC from scenario uncertainty or changes in the relative effect of different sources of uncertainty. When the U.S. federal government developed its SCC estimates it used a consistent set of five scenarios in three models, including FUND, and found the effect of varying the scenarios to be notably different across the models (USG, 2010, 2013). Implicit in these differences is uncertainty about the way in which climate change will ultimately affect human welfare and the most appropriate way to represent its impacts in IAMs. Understanding the interaction between this additional source of uncertainty and scenario uncertainty is an area where future research might be warranted.

It is also worth noting that while it is widely recognized that IAMs provide valuable information about the potential welfare losses associated with GHG emissions, they do not represent a complete accounting of the welfare risks, particularly when it comes to the difficulty in assessing unmanaged systems such as ecosystems, tropical cyclones, and oceans (Nordhaus, 2013). However, it is unlikely that such omissions would affect our finding that scenario uncertainty through its impact on the effective consumption discount rate has a significant effect on the expected benefits of CO_2 mitigation. Though, it may be the case that such omissions are important for understanding the relative effects of different sources of uncertainty.

Appendix A. Coastal Protection Algorithm and Sea Level Rise Damages

In FUND, the description of damages due to the inundation of land from sea level rise has roots in the model developed by Fankhauser (1995), but makes a number of major changes. This translation process has brought improvements to the original specification but has also introduced a potential source of uncertainty when considering scenario uncertainty and also an apparent misspecification in the level of damages experienced from dry land loss. In this section, we describe the method used by FUND to forecast the damages associated with land loss due to rising sea level, along with changes we made to the model in order to address the apparent misspecification and improve stability in the coastal protection algorithm.

A.1. *Wetland and dry land loss*

In the model of Fankhauser (1995), the change in wetlands was due to annual inland migration of existing wetlands on an unprotected coastline increasing their area over time and an inundation due to sea level rise which reduced their area. The damages associated with changes in the area of wetlands was $\mathrm{WL} = \Delta W_{t,r} R^W_{t,r}$, where $\Delta W_{t,r}$ [km^2] is the change in wetland area and $R^W_{t,r}$ [\$/km^2] is the value of ecosystem services from wetlands. In the approach taken by Fankhauser (1995) $\Delta W_{t,r}$ was used to represent cumulative change in wetland area through period t and $R^W_{t,r}$ represented an annual flow of consumption equivalent welfare per square kilometer of wetland. In FUND, $R^W_{t,r}$ was chosen to account for the present value of all future services that would have been provided by a unit of wetlands at the time it is lost. The value of wetlands is assumed to be increasing in the region's per capita income, $y_{r,t}$, and population density, $d_{r,t}$ [people/km^2] and decreasing in the region's existing wetland area, $W_{t,r}$. Specifically

$$R^W_{t,r} = \alpha \left(\frac{y_{t,r}}{y_{\tau,r}}\right)^{\beta} \left(\frac{d_{t,r}}{d_{\tau,r}}\right)^{\gamma} \left(\frac{W_{\tau,r} - \sum_{s=0}^{t-1} \Delta W_{s,r}}{W_{\tau,r}}\right)^{\mu}, \tag{A.1}$$

where α [\$/km^2] represents the present value of ecosystem services associated with a km^2 in the base year τ and $W_{\tau,r}$ [km^2] is the area of wetlands present in the region in the base year.[11]

To ensure cohesion with this approach the FUND model uses $\Delta W_{t,r}$ to represent not the cumulative change in wetlands through period t but instead the change in wetland area in period t. Therefore in FUND the change in wetlands is based not on the cumulative level of sea rise S_t, but instead the annual change in sea level ΔS_t. For every meter of sea level rise in a given year it is assumed that ω^s_r square kilometers of wetlands will become inundated and in turn lost forever. It is also assumed that if the region's coast were unprotected the wetlands would migrate such that ω^m_r additional square kilometers of wetlands would be gained per meter of sea level rise that occurred that year. It is further assumed that this gain will be limited by coastal protections in a proportional manner to the fraction of the coastline protected, following Fankhauser (1995). Therefore, the total area of wetlands lost in a given year

[11] Using this approach accounts for the loss of all future services that would have been provided by a unit of wetlands at its values at the time it is lost. Given future projections of increasing income and population, along with decreases in wetland area, this approach will represent an underestimate of the anticipated damages.

due to sea level rise is

$$\Delta W(\Delta S_t, \theta_{t,r}) = \min\left[\bar{W}_r - \sum_{s=0}^{t-1} \Delta W_{s,r}, \left(\omega_r^s + \theta_{t,r}\omega_r^m\right)\Delta S_t\right], \tag{A.2}$$

where $\bar{W}_r$ [km^2] is the area of the region's wetlands that are exposed to sea level rise, and $\theta_{t,r} \in [0, 1]$ is the fraction of the coastline that is assumed to be protected from current years increase in sea level. The min operator ensures that the region cannot lose more wetlands than those that are exposed to changes in sea level.

The general differences between FUND and the model of Fankhauser (1995) are similar in the case of dry land as they were for wetlands. The damages associated with changes in the area of dry land were $\mathrm{DL} = \Delta D_{t,r} R_{t,r}^D$, where $\Delta D_{t,r}$ [km^2] is the change in dry land area and $R_{t,r}^D$ [\$/km^2] is the value of dry land. In the approach taken by Fankhauser (1995) $\Delta D_{t,r}$ was used to represent cumulative loss of dry area through period t and $R_{t,r}^D$ represented an annual flow of consumption equivalent welfare per square kilometer of dry land. Analogous to the case with wetlands, in FUND $R_{t,r}^D$ was chosen to account for the present value of all future services that would have been provided by a unit of dry land at the time it is lost. The value of dry land is assumed to change over time only with changes in the region's income density, such that

$$R_{t,r}^D = \phi\left(\frac{Y_{t,r}/A_{t,r}}{\Lambda}\right)^{\zeta}, \tag{A.3}$$

where ϕ [\$/km^2] is the baseline value of dry land for the reference level of income density Λ [\$/km^2], $Y_{t,r}$ [\$] is the region's GDP, $A_{t,r}$ [km^2] is the region's area net of land loss to date, and ζ is the elasticity of dry land value with respect to income density. One important difference between FUND and the model of Fankhauser (1995) is that in the latter it was assumed that regional decision makers would choose to build sea walls such that they protect the most valuable land first. Therefore, the value of dry land was decreasing in the fraction of the coast line protected. In FUND, the value of dry land per km^2 is assumed to be independent of the level of coastal protections.

In FUND, the annual area of dry land lost, $\Delta D(\Delta S_t, \theta_{t,r}) = \Delta D_{t,r}$ [km^2], occurs simply due to the inundation of land by the sea, and is assumed to be a power function with respect to sea level rise in a given year. Specifically if no coastal protections are erected in year t the area of dry land lost is

$$\min\left[\bar{D}_r - \sum_{s=0}^{t-1} \Delta D_{s,r}, \psi(\Delta S_t)^{\nu}\right], \tag{A.4}$$

where $\bar{D}_r$ represents the total area of dry land in the region that is exposed to sea level rise. However, since the region has the ability to erect coastal protections that can protect the threatened land such that the actual loss of dry land will be

$$\Delta D(\Delta S_t, \theta_{t,r}) = (1-\theta_{t,r}) \min\left[\bar{D}_r - \sum_{s=0}^{t-1} \Delta D_{s,r}, \psi(\Delta S_t)^{\nu}\right]. \tag{A.5}$$

A.2. *"Optimal" level of coastal protection*

In FUND, the cost of coastal protections are similar to those used by Fankhauser (1995). In FUND, it is assumed that the cost for a region to protect its entire coastline for one meter of sea level rise in a given year, π_r [\$/m], will be constant over time and sea level. It is assumed that if the region erects coastal protections for any part of their coastline they will do so as to protect against the full increase in sea level for that year. Furthermore, it is assumed that the cost will scale proportionally with the fraction of the coastline protected such that the total cost of protection in a given year will be

$$\theta_{t,r}\pi_r\Delta S_t. \tag{A.6}$$

In FUND, as with the work by Fankhauser (1995), the optimal level of coastal protection is said to be chosen through a simple cost benefit analysis used to mimic the behavior of regional decision makers. The FUND documentation does not provide the details of the objective function used by the regional decision makers, but does posit that the solution is equivalent to the form derived by Fankhauser (1995). Specifically the FUND model assumes the "optimal" solution to be

$$\theta^*_{t,r} = 1 - \frac{\sum_{t=0}^{\infty}(\frac{1}{1+\delta_t})^t \mathrm{PC}(1,\Delta S_t) + \sum_{t=0}^{\infty}(\frac{1}{1+\delta_t})^t \mathrm{WG}(1,\Delta S_t)}{2\sum_{t=0}^{\infty}(\frac{1}{1+\delta_t})^t \mathrm{DL}(0,\Delta S_t)} \tag{A.7}$$

for interior solutions and $\theta^*_r = 0$ otherwise. Based on (A.6), the cost of protecting the coastline is

$$\mathrm{PC}(\theta_{t,r}, \Delta S_t) = \theta_{t,r}\pi_r\Delta S_t. \tag{A.8}$$

The lost value of inland wetland migration due to sea level rise that would be lost from coastal protections is derived from (A.1) and (A.2) such that

$$\mathrm{WG}(\theta_{t,r}, \Delta S_t) = \theta_{t,r}\omega^m_r \Delta S_s R^W_{r,t}. \tag{A.9}$$

The value of lost dry land due to sea level rise is derived from (A.3) and (A.4) such that

$$\mathrm{DL}(\theta_{t,r}, \Delta S_t) = (1-\theta_{t,r}) \min\left[\bar{D}_r - \sum_{s=0}^{t-1} \Delta D_{s,r}, \psi(\Delta S_s)^{\nu}\right] R^D_{t,r}. \tag{A.10}$$

As noted above, in FUND, the simplifying assumption is made that regional decision maker's expectation in every period is that future income per capita growth and sea level rise will be equivalent to what is being experienced in the current period, such that $g_{s,r} = g_{t,r} \forall s \geq t$ and $\Delta S_s = \Delta S_t \forall s \geq t$. It is also assumed that the regional decision maker is choosing the "optimal" level of protection as if it will be constant from the current period into the future, $\theta_{s,r} = \theta_{t,r} \forall s \geq t$. Given this assumption (A.7) may be rewritten as

$$\theta^*_{t,r} = 1 - \frac{(\frac{1+\delta_t}{\delta_t})\pi_r \Delta S_t + [\frac{1+\delta_t}{\delta_t - \eta(\frac{Y_t A_{t-1}}{Y_{t-1}A_t} - 1)}]\omega^m_r \Delta S_t R^W_{t,r}}{2[\frac{1+\delta_t}{\delta_t - \beta g_t - \gamma(\frac{d_t}{d_{t-1}} - 1) - \mu w_{t-1}}]\min[\bar{D}_r - \sum_{s=0}^{t-1}\Delta D_{s,r}, \psi(\Delta S_s)^\nu]R^D_{r,t}}, \tag{A.11}$$

where w_{t-1} represents the growth of wetlands such that,

$$w_t = \frac{\Delta W_t}{W_{\tau,r} - \sum_{s=0}^{t-1}\Delta W_s} - 1. \tag{A.12}$$

This solution as implemented in the model's source code is potentially problematic as it does not solve the correct implicit objective function described in the model. Given the description of the coastal protection problem described above the minimization problem for the regional decision maker may be written as

$$\min_{\theta_{t,r}} \sum_{s=0}^{\infty}\left(\frac{1}{1+\delta_t}\right)^s [\mathrm{PC}(\theta_{t,r}, \Delta S_t) + \mathrm{DL}(\theta_{t,r}, \Delta S_t) + \mathrm{WL}(\theta_{t,r}, \Delta S_t)], \tag{A.13}$$

where

$$\mathrm{WL}(\theta_{t,r}, \Delta S_t) = \min\left[\bar{W}_r - \sum_{s=0}^{t-1}\Delta W_{s,r}, (\omega^s_r + \theta_{t,r}\omega^m_r)\Delta S_t\right] R^W_{t,r}. \tag{A.14}$$

The assumption that regional decision maker in any given period will expect the future conditions (e.g., growth of sea level, income growth, etc.) to be the same as the current period means that everything in the problem is constant except for the exponent on the discounting component and expected changes to the value of wetlands and dry land. Therefore, the problem in (A.13) may be rewritten as

$$\min_{\theta_{t,r}} \left\{\frac{1+\delta_t}{\delta_t}\mathrm{PC}(\theta_{t,r}, \Delta S_t) + \frac{1+\delta_t}{\delta_t - \beta g_t - \gamma(\frac{d_t}{d_{t-1}} - 1) - \mu w_{t-1}}\mathrm{DL}(\theta_{t,r}, \Delta S_t)\right.$$
$$\left. + \frac{1+\delta_t}{\delta_t - \zeta(\frac{Y_t A_{t-1}}{Y_{t-1}A_t} - 1)}\mathrm{WL}(\theta_{t,r}, \Delta S_t)\right\}. \tag{A.15}$$

Substituting in for the functional arguments yields

$$\min_{\theta_{t,r}}(1+\delta_t)\left\{\frac{\theta_{t,r}\pi_r \Delta S_t}{\delta_t} + \frac{(1-\theta_{t,r})}{\delta_t - \beta g_t - \gamma(\frac{d_t}{d_{t-1}} - 1) - \mu w_{t-1}}\right.$$
$$\times \min\left[\bar{D}_r - \sum_{s=0}^{t-1}\Delta D_{s,r}, \psi(\Delta S_s)^\nu\right]\phi\left(\frac{Y_{t,r}/A_{t,r}}{\Lambda}\right)^\zeta$$

$$+\frac{\min\left[\bar{W}_r-\sum_{s=0}^{t-1}\Delta W_{s,r},(\omega_r^s+\theta_{t,r}\omega_r^m)\Delta S_t\right]}{\delta_t-\zeta(\frac{Y_tA_{t-1}}{Y_{t-1}A_t}-1)}\alpha\left(\frac{y_{t,r}}{y_{\tau,r}}\right)^\beta \times\left(\frac{d_{t,r}}{d_{\tau,r}}\right)^\gamma\left(\frac{W_{\tau,r}-\sum_{s=0}^{t-1}\Delta W_{s,r}}{W_{\tau,r}}\right)^\mu\Bigg\}. \tag{A.16}$$

The important characteristic to note is that because the FUND model assumes that the value of dry land will be constant independent of the fraction of the coastline already protected, unlike in the model by Fankhauser (1995), this objective function is now linear in the control variable, $\theta_{t,r}$. Therefore the actual optimal level of protection given the assumptions in the FUND model is not the one in (A.11), but instead a corner solution at either no protection, $\theta_{t,r}=0$, or protection of the entire coastline, $\theta_{t,r}=1$. This is due to the fact that in the FUND model there is assumed to be no difference across each unit of dry land. Therefore, if it is optimal to (not) protect any unit of land, then it is optimal to (not) protect every unit of dry land susceptible to sea level rise. The level of protection then that actually comes out of the simple cost benefit analysis as defined in the FUND model is

$$\theta_{t,r}^*=\begin{cases}0 & \dfrac{\mathrm{PC}(1,\Delta S_t)}{\delta_t}+\dfrac{\mathrm{WG}(1,\Delta S_t)}{\delta_t-\zeta(\frac{Y_tA_{t-1}}{Y_{t-1}A_t}-1)}>\dfrac{\mathrm{DL}(1,\Delta S_t)}{\delta_t-\beta g_t-\gamma(\frac{d_t}{d_{t-1}}-1)-\mu w_{t-1}}\\ 1 & \text{otherwise}\end{cases}. \tag{A.17}$$

We consider the assumption of uniformly valuable coast land to be unrealistic and interpret this assumption implicit in the definition of (A.3) to be a misspecification. Instead we use the description of dry land value as defined by Fankhauser (1995) where land value is non-uniform and decreases with coastal protection efforts representing a situation in which the regional decision makers protect the most valuable land first. Therefore, instead of (A.3) we define the value of dry land as

$$R_{t,r}^D=(1-\theta_{t,r})\phi\left(\frac{Y_{t,r}/A_{t,r}}{\Lambda}\right)^\zeta, \tag{A.18}$$

in order to match the assumptions used by Fankhauser (1995). In this case, the potential interior solution in (A.11) is now be correct for the specification of the model.

Also of concern is the assumption that the regional decision makers examine the current state of the world (e.g., GDP growth, sea level growth, etc.) and forecast future conditions assuming that these current conditions will continue into perpetuity. This assumption coupled with the ability of the decision makers to update their coastal protection plan each period leads to cases in which they are forecast to react strongly to even a slight deviation from long-term trends as they assume this to be the new normal going forward. This specification, while seemingly unrealistic, may be an acceptable approximation for situations in which the path of the state variables is relatively smooth over time. However, in the case scenario uncertainty this specification can lead to model instability as a stochastic shock in a given period can lead to a disproportionate reaction projected for regional decision makers as they assume that this shock is a permanent deviation from the long-term trend. Therefore, we introduce additional stability into the algorithm by assuming that regional decision makers do not rely on only the current period's state variables to forecast future conditions, but instead a 20 year moving average. Therefore, the protection level is determined by the equation

$$\theta^{*}_{t,r} = 1 - \frac{\left(\frac{1+\delta_t}{\delta_t}\right)\pi_r \frac{1}{20}\sum_{i=0}^{19}\Delta S_{t-i} + \left[\frac{1+\delta_t}{\delta_t - \zeta\sum_{i=0}^{19} a_{t-i}}\right]\omega_r^m \frac{1}{20}\sum_{i=0}^{19}\Delta S_t R^W_{t,r}}{2\left[\frac{1+\delta_t}{\delta_t - \beta\frac{1}{20}\sum_{i=0}^{19} g_{t-1-i} - \gamma\frac{1}{20}\sum_{i=0}^{19}\left(\frac{d_{t-i}}{d_{t-1-i}}-1\right) - \mu\frac{1}{20}\sum_{i=0}^{19} w_{t-1-i}}\right] \times \min[\bar{D}_r - \sum_{s=0}^{t-1}\Delta D_{s,r}, \psi(\frac{1}{20}\sum_{i=0}^{19}\Delta S_{s-i})^{\nu}]R^D_{r,t}}, \quad \text{(A.19)}$$

where a_t is income density growth in period t,

$$a_t = \frac{Y_t/A_t}{Y_{t-1}/A_{t-1}} - 1.$$

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